Surface Roughness Intelligent Prediction on Grinding

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Abstract. Grinding is generally the final process, and it is closely related with the surface quality of the component. Now, it's difficult to measure the surface roughness until the grinding process is finished. The purpose of this research was to study the roughness prediction and avoid the defect happening in the grinding process. A surface roughness prediction model was built using the acoustic emission (AE) signal and Fuzzy- neural networks. Tests were performed, and the result verifies the feasibility of the proposed model.

Introduction

The grinding operation gives workpieces their final finish surface roughness through the interaction between the abrasive grains of grinding wheel and the workpiece. However, Grinding process is non-linear, random and indeterminate , and it's difficult to build exact mathematic model. Now, all the existing measuring methods can't be conducted until the grinding process is finished. This means following problems will occur: time, labor, and material have to be spent continuously after a defect happens in the grinding process; the measured results are not the current surface quality information, which are needed in the modern manufacturing process. To settle this problem, many experts studied the roughness and built some surface roughness theory models and experimental models [1-6], but their accuracy is low and can't widely apply in the practice grinding process.

In this paper, we propose an intelligent roughness prediction model based on acoustic emission (AE) signals, in which not only the grinding parameters but also the AE signals are added to the inputs.

Intelligent Predication Model's Building

Theory Basis. Extensive studies have been carried out in the workpiece surface roughness for the grinding process. For cylindrical traverse grinding, Malkin developed a surface roughness theory equation as follows [7]

$$R_a = \left(\frac{R_0}{m^{1/2}}\right)\left(\frac{v_w L}{v_s d_e^{1/2}} \cdot \frac{f_a}{b_s}\right)^{0.8} + R_\infty \tag{1}$$

Here, R_0 and R_∞ are experience constants respectively; m is a constant ; v_w is the workpiece velocity; v_s is the grinding wheel velocity; L is the grain uniformity distribution distance along the grinding wheel circumference; d_e is the grinding wheel diameter; f_a is the table feed ; b_s is the grinding wheel width. Eq.1 was obtained under the ideal condition without principal axis jumpiness, vibration and plastic deformation, and actual roughness value will be much bigger than that. But the theory equation is useful in analysis the relations between the surface roughness and grinding parameters. From Eq.1, we get that roughness is in direct proportion to workpiece velocity v_w and table feed f_a, and in inverse proportion to grinding wheel velocity v_s .

Literature [8,9] indicates that the surface roughness data are apt to obey the following.

$$R_a = R_1(\frac{v_w a_p}{v_s})^x \tag{2}$$

Where, R1 and x are, respectively, the constants determined by the experiment. ap is grinding depth. From Eq.2, we get that the roughness is in direct proportion to grinding depth ap .

Since the wear of the grinding wheel has a direct effect on the workpiece surface roughness, the signal of acoustic emission can show the wear degree of grinding wheel.

Considering all of the above relationships, we proposed the relations of roughness and machining parameters as follows

$$R_a = R(\frac{V_w}{V_s})^x \quad (a_p)^y (V_f)^z W_{AE} \tag{3}$$

Where, R, x, y, z are experimental constants respectively. WAE is the wear degree of grinding wheel. This relationship is the theory basis of our proposed roughness prediction model in this paper.

Architecture and Algorithm. In Eq.3, R, x, y, z and m are the experimental constants, which are on the case-by-case basis. The values of R, x, and y established under one grinding condition generally cannot be used for roughness prediction of other conditions. To settle the problem, the fuzzy neural network is introduced in modeling process, because the fuzzy neural network has self-learning and self-adapted ability. In this fuzzy neural network, the neural network is used to implement fuzzy inference. The parameters in fuzzy inference are expressed with neural network connection weights. Eq.3 is calculated logarithm in the two sides. Supposing lgR=R1, we can get the following.

$$\lg R_a = R_1 + x\lg(\frac{v_w}{v_s}) \quad + y\lg a_p + z\lg V_f + \lg W_{AE} \tag{4}$$

We use the logarithm of the velocity ratio of (vw/vs), the logarithm of grinding depth ap, the logarithm of traverse feed velocity fa and the logarithm of wear degree of grinding wheel WAE as inputs of fuzzy neural network, and the logarithm of the roughness is as the output, shown in Fig.1.

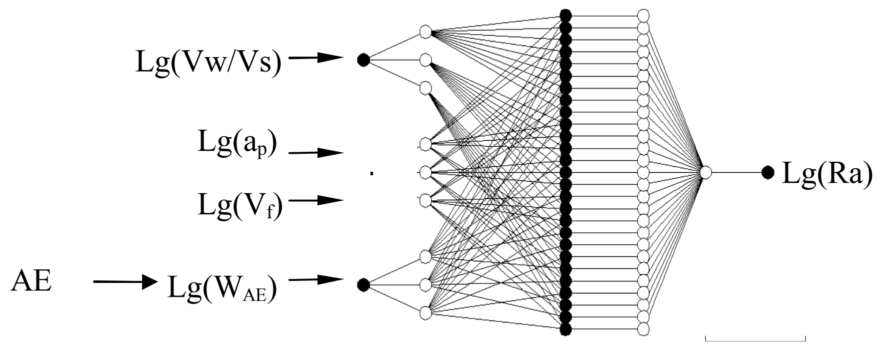

Fig.1 Architecture of the fuzzy neural network based on AE

From the Eq. 4, we know that there exists linear relation between the roughness logarithm and the logarithm of (vw/vs), ap, fa and WAE. So, we adopt T-S type fuzzy inference to obtain R1, x, y and z. The rule form is as followings: If x1=A1 , x2=A2 , x3=A3 , then fj= pjx1 + qjx2 + rjx3 + sj

Experiment

The experiments had been finished on the MGK1420 high precision CNC cylindrical grinder. The signals of acoustic emission were collected and analyzed by Beijing Shenghua SAEU2S system, and the sensor is SR800. The grinding liquid is emulsion. The wheel's dressing depth and lead are 0.01mm and 0.08mm respectively. The material of the workpiece is 45 steel.

The main grinding parameters vw, vf and ap related to the roughness can be changed by this experimental grinder. The experiment was finished with workpiece velocity v_w 125 r/m,170r/m and 200r/m, table feed fa 6 mm/r ,9.6mm/r,13.6mm/r,17.6mm/r ,21.6mm/r and 26.8mm/r, and grinding depth ap 0.01mm,0.02mm and 0.03mm, respectively. The workpiece surface roughness R was measured with surface roughness detector TR240. We obtained 90 specimen groups, among which, 60 specimen groups were used to train the fuzzy neural networks, and 30 specimen groups were used to test the fuzzy neural networks.

Table 1 shows the roughness results of the fuzzy neural network predictive model and actual measurement. It can be seen from Table 1 that the prediction roughness results of the proposed fuzzy neural network predictive model with AE in this paper are very close to the measured one.

Table 1 Roughness result of the intelligent prediction model (Ra μm)

	1	2	3	4	5	6	7	8	9	10
Measure value	0.092	0.121	0.113	0.130	0.074	0.101	0.103	0.107	0.118	0.148
Prediction value	0.090	0.117	0.109	0.131	0.080	0.100	0.107	0.107	0.118	0.137
Relative error	-0.024	-0.033	-0.034	0.002	0.074	-0.007	0.033	-0.001	0.001	-0.076

	11	12	13	14	15	16	17	18	19	20
Measure value	0.126	0.149	0.161	0.193	0.043	0.172	0.168	0.210	0.047	0.126
Prediction value	0.127	0.152	0.160	0.191	0.042	0.172	0.167	0.211	0.046	0.125
Relative error	0.015	0.023	-0.003	-0.013	-0.007	0.003	-0.006	0.008	-0.018	-0.009

	21	22	23	24	25	26	27	28	29	30
Measure value	0.141	0.174	0.169	0.170	0.062	0.080	0.099	0.093	0.101	0.125
Prediction value	0.143	0.171	0.171	0.172	0.060	0.082	0.101	0.093	0.104	0.125
Relative error	0.009	-0.016	0.010	0.010	-0.023	0.022	0.023	0.003	0.029	0.006

The correctness and coverage of the training data affect the model accuracy directly since the accuracy of proposed prediction model depands on training data.

Conclusion

This paper builds the intelligent predictive model of surface roughness in grinding process based on AE. The experimental results prove that the proposed fuzzy neural networks prediction model based on AE is feasible and have higher prediction accuracy.

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